Courting Two-Timers: 
Multi-homing Users’ Preferences for Two-Sided Exchange Networks

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ABSTRACT

Our research analyzes users’ preferences for two-sided exchange networks that serve distinct but inter-dependent types of users (e.g. buyers and suppliers). To do this we look at multi-homing users’ participation on multiple independent and competing platforms. We use a unique dataset of 118 multi-homing buyers’ participation in two online exchanges and examine how activity levels on both sides of these exchanges affect users’ preferences for the exchanges.

We find that users’ preferences are positively associated with activity levels on the opposite side of the platforms. Higher inter-network activity levels positively affect users’ perception of a platform’s usefulness and motivate increased participation on that platform relative to the competing platform. We also find that users’ preferences are non-linearly related to activity levels on the same side of the platform. At low intra-network activity levels, an increase in activity level has a positive effect on users’ preferences. This effect may derive from the principle of social proof, where individual users observe and imitate other similar users’ behaviors. At high intra-network activity levels, there is a negative effect of increased activity level due to greater competition among users on the same side. Our results show how competition between networks serving the same users is affected by the social information conveyed by other users participating on each network. It complements the existing IS literature, which typically focuses on single-homing users and/or one-sided network technologies.

Keywords: user acceptance of IT, electronic markets and auctions, 2-sided networks, multi-homing, network externalities, social proof, social influence, online exchanges, system usage, technology acceptance model

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INTRODUCTION

“Nobody goes there anymore, it's too crowded” — attributed to Yogi Berra.

Business-to-business (B2B) networks are proliferating, giving buyers and suppliers more options, and raising an important managerial question: How do buyers choose between competing networks? Given that buyers can participate in multiple exchanges, how do buyers decide which exchanges to use, and which exchanges to use more? To investigate these questions, we use concepts on technology acceptance and usage (Davis 1989; Venkatesh et al. 2003) and a set of results in social psychology, often called social proof (Cialdini 2008). We show that apart from looking at the participation of suppliers on the exchanges, buyers also rely on the information conveyed by the participation of other buyers in deciding which exchanges to use and how much to use them.

Our paper centers on the empirical analysis of user choice and usage of two-sided exchange networks, in particular, B2B exchanges. Two-sided networks are platforms that facilitate interactions between distinct but inter-dependent groups of users (Rochet and Tirole 2003). Similar types of exchange networks include social lending clubs (e.g., Lending Club, Prosper Marketplace) and online marketplaces (e.g., Amazon Marketplace, eBay).

In this paper, we focus on the preferences of users who use multiple exchange networks, termed multi-homing users. This focus departs from existing research on technology and system usage in two ways. First, existing studies of IT users’ behaviors tend to focus on one-sided networks with a single type of user such as online brokerages (Chen and Hitt 2002), telecommunication systems (Kraut et al. 1998), collaborative technology (Devaraj et al. 2008), and data and information retrieval systems (Venkatesh and Morris 2000). In contrast to these studies we look at systems that have the characteristics of two-sided networks, an important trend in today’s business environment (McKinsey Quarterly, 2010). Some insights from one-sided networks may not be applicable in two-sided network contexts given the social and

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1 In this paper, we use networks and platforms interchangeably.
market dynamics that take place across and within the distinct sides on the platforms. For instance, the relationship between price and cost on two-sided platforms is complex, such that optimal prices depend on demand elasticity on both sides of the platform and the profit maximizing price may be below marginal cost (Chandra and Collard-Wexler 2009; Evans and Schmalensee 2007).

Second, many studies of technology acceptance and usage look at system adoption decisions of single-homing users: those who adopt and use only one system for a particular need (e.g. selling on Amazon or eBay). For example, Karahanna et al. (1999) look at the adoption of an operating system within a firm, while Venkatesh and Morris (2000) study the implementation of a data and information retrieval system in five organizations. Although system adoption decisions and sustained usage are systematically different (Bhattacherjee 2001; Venkatesh and Morris 2000), these decisions should be related for single-homing users, particularly in the short run. As such, focusing on system adoption intention and behavior of single-homing users is not a problem. However, this focus is insufficient when studying multi-homing users, as multi-homing users may use various systems to varying extents, and it is the relative usage levels that matter in competition among technologies or platforms (Kraut et al. 1998). Because multi-homing behaviors are common in many two-sided networks, it is essential to look beyond system adoption decisions, and examine multi-homing users’ preferences and long-term usage of competing networks.

Thus, our objective in this study is to examine factors that affect multi-homing users’ preferences among platforms when they are using two-sided exchange networks. In particular, how do the levels of buying and selling activities on both sides of these exchanges affect buyers who are using multiple platforms? While increasing selling activity levels on the opposite side of the platforms should have positive effects on multi-homing buyers’ preferences, buying activity levels on the same side of the platforms can have positive or negative effects depending on the level of participation of other buyers. In particular, very low levels of buyer activity will negatively affect buyers’ inclination to participate. As buying activity increases up to a point, the increased activity will attract the buyers to participate more. At that point, further increases in buyer activity will discourage buyers from participating in the market. We derive this
result as a consequence of the joint operation of two processes: social proof and between-buyer competition. We also investigate how misspecification of users’ homing behaviors may affect the results. Our findings have implications for understanding competition among two-sided networks as well as platform design and strategy. To the best of our knowledge, this is the first study that examines (i) users’ preferences for two-sided networks in multi-homing situations, and (ii) social proof as an influence of technology and system usage.

**LITERATURE REVIEW**

**Homing Behaviors on Platforms and Systems**

Single-homing refers to a situation in which an individual uses only one platform, while multi-homing has been described as a situation in which an individual is affiliated with or uses several platforms (Armstrong 2006; Choi 2010; Rochet and Tirole 2003). Yet it is not always the case that a user is multi-homing whenever she uses more than one platform. For example, consider a buyer who searches for chemical suppliers on one B2B exchange, and mineral suppliers on another exchange. Or suppose a programmer uses Macintosh OS for graphic-intensive tasks but Windows OS for other tasks. We term such situations as task-dependent homing – although individuals are using several systems, the chosen system depends on the task at hand.

A user is said to be multi-homing when she uses two or more independent and competing platforms or systems for a specific task or tasks. By our definition, each of the systems that a multi-homing user is using can independently handle the user’s task. (This condition differs from situations where multiple systems are jointly needed to accomplish certain tasks.) By using multiple independent systems, the user is allowing competition among the systems (Rochet and Tirole 2006). For a user’s behavior to be described as “multi-homing,” she should be using competing systems for the same tasks. For instance, a buyer is multi-homing when she sources for suppliers of a specific product on multiple exchanges. Likewise, a computer enthusiast is multi-homing when he installs various OS on his computers, and each
OS allows him to do the same tasks (e.g. coding or web-surfing). Table 1 illustrates different homing behaviors by users of various systems and platforms.

**Table 1: Examples of Homing Behaviors**

<table>
<thead>
<tr>
<th>Technology</th>
<th>Single-homing</th>
<th>Task-dependent homing</th>
<th>Multi-homing</th>
</tr>
</thead>
<tbody>
<tr>
<td>B2B Exchange</td>
<td>One exchange to source for chemical suppliers.</td>
<td>One exchange to source for chemical suppliers and another exchange for mineral suppliers.</td>
<td>Several exchanges to source for chemical suppliers.</td>
</tr>
</tbody>
</table>

**Technology and System Usage**

System usage refers to the use of a system by an individual to perform a task (Burton-Jones and Gallivan 2007). Users’ intended and actual usage of a system is affected by the perceived usefulness of the system and the perceived ease of use of the system (Davis 1989; Davis et al. 1989; Gefen et al. 2003; Karahanna and Straub 1999; Thong et al. 2006; Venkatesh and Davis 2000; Venkatesh et al. 2003). System usage is also affected by social influence, or subjective norms, which refers to the degree to which users perceive that important others believe they should use a particular system (Thompson et al. 1991; Venkatesh and Davis 2000). Users’ intentions to use a system are higher when people who are important to them think they should use it (e.g. Devaraj et al. 2008; Venkatesh and Davis 2000; Venkatesh and Morris 2000; Venkatesh et al. 2003), or when they are well-connected to coworkers who are knowledgeable about that specific system (Sykes et al. 2009).

These determinants of system usage (perceived usefulness, perceived ease of use, and social influences) are in turn affected by factors such as system developers’ responsiveness to users’ inputs (Gefen and Keil 1998), personality (Devaraj et al. 2008), self-efficacy (Igbaria and Iivari 1995; Thompson et al. 2006), gender, and experience with the system (Venkatesh and Morris 2000; Venkatesh et al. 2003). For
example, the social influence effect on system usage is stronger when users are new to the system. As users gain direct experience with the system over time, influences from others have weaker effects on these users’ intentions to use the system (Venkatesh and Davis 2000; Venkatesh and Morris 2000). Acceptance of a new system sometimes means that an existing system is being replaced (e.g. Venkatesh and Davis 2000). With new systems constantly arriving in the marketplace, it is essential for system providers to motivate both new and experienced users to actively use their systems. The existing literature in system usage, though, has two noteworthy limitations. First, current research tends to pay more attention to system usage during the first six months of system implementation, when users may be relatively unfamiliar with the new systems (e.g. Bajaj and Nidumolu 1998; Sykes et al. 2009; Szajna 1996; Venkatesh and Davis 2000; Venkatesh and Morris 2000; Venkatesh et al. 2003). A notable exception is Kraut et al.’s (1998) study, which investigates the introduction and use of communication systems in a company over a period of 18 months. Comparatively, there are relatively few studies on system usage that also include users who may be familiar with the technology that is being examined (e.g. Hong et al. 2006; Taylor and Todd 1995; Thompson et al. 1991).

Second, few studies specifically examine multi-homing behaviors by users who use multiple systems simultaneously (e.g. Chen and Hitt 2002; Kraut et al. 1998). Instead, most studies look at individuals’ usage of a single system, without explicitly considering whether users might be using competitive systems during or subsequent to the time of the study (e.g. Sykes et al. 2009; Taylor and Todd 1995; Venkatesh et al. 2003). For example, in Sykes et al.’s (2009) study, using a newly implemented system was voluntary and employees could continue using existing systems for their job; however, the study does not examine employees’ usage of existing systems. Considering potential multi-homing behaviors should be important to the literature as such behaviors may affect relative system usage and competition among systems (Kraut et al. 1998). Thus, our study adds to the existing literature (i.e. new users in single-homing contexts) by looking at system usage by individuals who (i) have different levels of experience with the systems and (ii) concurrently use multiple competitive systems.
Two-Sided Networks

Two-sided networks can be categorized into four different types (Evans and Schmalensee 2007):

1. Exchanges (e.g. Alibaba.com, Amazon Marketplace, eBay) that provide match-making services that help buyers and sellers enter into mutually beneficial trades.

2. Advertising-supported media such as newspapers and web portals (e.g. New York Times, Yahoo). These platforms provide content to attract viewers, who in turn attract companies to advertise on the platforms.

3. Transaction or payment systems (e.g. Visa, MasterCard) that provide the mechanism for merchants and customers to fulfill the financial aspects of the transactions.

4. Software platform (e.g. operating system, game consoles) that facilitate interactions between applications developers and users. Software platforms are key in many industries, such as personal computers, video games, and digital entertainment.

In each of these platforms, there are distinct but inter-dependent types of users. These users derive value mainly by interacting with other users on the opposite side of the platform. However, there are significant differences among these platforms in terms of how users interact with other users on the same side of the platforms. On exchanges, users often compete with other users on the same side for access to the opposite side. For example, buyers on eBay compete for items that sellers are auctioning, and sellers compete for buyers’ bids. For advertising-supported media and payment systems, there is usually competition on one side of the platform but limited or neutral interaction the other side. For instance, advertisers compete for viewer’s attention (Dukes and Gal-Or 2003), but viewers do not compete with each other when viewing advertisements. Merchants compete to some extent for shares of customers’ spending, but customers are not concerned with whether the next customer in line is using the same or a different payment system (Rochet and Tirole 2002). Finally, for software platforms, there often is competitive interaction on one
side of the platform, and cooperative interaction on the other. Developers compete for market share while users share files or participate in multi-players game.

These differences in interactions among users on the same side on different platforms have implications for two-sided network research. The relatively symmetric interactions for buyers and sellers on exchanges, for instance, suggest that insights into one side of the exchanges may be generalized to the other side to some extent. However, this may not be the case for other types of platforms.

**Network Externalities in Two-Sided Networks**

When the value of a product to a user depends on the total number of users (Katz and Shapiro 1985), this is termed as network externality. Typically, users attach higher values to technologies as the installed user bases increase. Network externalities are prominent in technologies such as software and telecommunications, and have been widely discussed (e.g., Asvanund et al. 2004; Brynjolfsson and Kemerer 1996). Network externalities in two-sided networks can be categorized as either inter-network externalities or intra-network externalities.\(^2\) *Inter-network externalities* refer to how characteristics of one side of the platform affect users on the other side. For instance, having more buyers or buying activities on an exchange would affect suppliers, and vice versa. In most cases, inter-network externalities are positive — i.e. the expected gain for users on one side of the platform is higher when there are more users or higher activity levels on the opposite side. For example, in web-server software markets, users have higher perceived value for servers when a platform has higher browser market-share (Gallaugher and Wang 2002).

Positive inter-network externalities can lead to a “chicken-and-egg problem” in two-sided networks: to attract users of one type, the platform needs to have a sufficient number of users of the other type.

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\(^2\) The concepts of inter-network and intra-network externalities are similar to those of indirect network and direct network externalities, respectively. The latter terminology, however, do not depend on the existence of a platform that connects distinct but inter-dependent groups of users. For instance, indirect network effects can refer to how the availability or prices of complementary goods affect the value of a main good. To emphasize the two-sided nature of the platforms that we focus on in this study, we stick to the terminology of inter- and intra-network externalities.
(Caillaud and Jullien 2003). This means that platforms need to get “both sides on board,” attracting users on both sides to adopt their platforms simultaneously. There are pricing strategies and structures that can overcome this problem (Armstrong 2006; Caillaud and Jullien 2003; Chao and Derdenger 2010; Rochet and Tirole 2003, 2006).

*Intra-network externalities* refer to how characteristics of one side of the platform affect users located on that same side. In an online exchange, intra-network externalities relate to how having more buyers or buying activities in the exchanges would affect buyers’ experiences, or how having more suppliers or selling activities would affect suppliers’ benefits. While most studies of two-sided networks focus on inter-network externalities, intra-network externalities are “either abstracted away or not central to the analysis” (Belleflamme and Toulemonde 2009: 247). We suspect that since users usually derive benefits and value on two-sided networks via interactions that occur across the platforms, there is greater interest and focus on inter-network rather than intra-network dynamics. In analytic studies of the dynamics of buyer-seller exchange, it is often assumed that intra-network externalities are negative: as the number of users on one side of an exchange increases, these users face greater competition and derive lower benefits on the exchange (see Anderson et al. 2008; Belleflamme and Toulemonde 2009). In effect, as the number of buyers increases, prices are bid up. On the sell side, more sellers imply lower profit margins for any seller. In an empirical study, Tucker and Zhang (2010) find that the presence of many sellers has negative effects on whether a potential seller participates on the exchange. In addition, these studies typically assume users are single-homing to simplify their analysis. In contrast, we consider the possibility of *positive* intra-network externalities and focus on multi-homing behaviors of users in two-sided exchange networks in this study.

**Social Proof**

To this point, we have focused on how price factors and competition affect market participants’ decisions. However, there is always some residual uncertainty in market transactions. To reduce this uncertainty,
market participants use different sources of information they can acquire, such as market and seller reputation, contractual safeguards, and verification. Social proof is another informative factor that can influence choice and behavior. Cialdini (2008: 99) points out that “we determine what is correct by finding out what other people think is correct.” When we see others behave in a certain way towards a situation, those behaviors are informative to us. For instance, when we see a crowded restaurant, that tells us that the restaurant is probably good; the actions of others provide social proof to that point. In an abstract way, prices themselves are indicators of the value placed by others on a good or service. One can think of market behavior as a form of social proof.

Social proof is not conforming to the opinion of others, following fashion, or an information cascade. If you walk down an empty street with litter, you are more likely to litter than if that street was clean (Keizer et al. 2008). The presence of litter signals to you that this is correct or acceptable behavior. If you litter with no one else to observe you, your littering cannot be explained as conforming to the expectations of others, since no one is there to reward or sanction you. Similarly, following fashion cannot account for littering on an empty, littered street. If you litter on an empty street, no one can see you make this “fashionable choice.” To be part of those who follow fashion or are “in the know” requires others to observe you; otherwise there are no incentives to engage in following fashion or fads.

This kind of effect, not accounted for by conformity pressures or fashion, has been demonstrated in a number of studies (Cialdini 2008). Experimental studies have found that observing the consequences of others’ actions, such as litter on an empty street, with no bystanders, is sufficient to influence people to litter (Keizer et al. 2008). A popular version of this idea is sometimes referred to as “broken windows” theory (Gladwell 2000). This theory argues that when residents of a city see broken windows and graffiti everywhere, this signals that the city and its residents accept lawless and criminal behavior. The implication is that to reduce crime, one thing a city can do is to clean up, fix all the windows, erase the graffiti and present social proof that lawless behavior is not tolerated.
Social proof is also different from an information cascade (Bikhchandani et al. 1992) which requires (i) observation of the actions of others, and (ii) the observer’s action being conditioned on that observation (making the same choice another makes because you observe their choice) while ignoring private information. While both social proof and information cascades reflect inferences from observing others’ behaviors, we will show below that social proof is not an information cascade. Instead, social proof is only one piece of information in the decisions we discuss below. Observing others’ decisions, while informative, will not necessarily lead to a cascade and an observer will still consider private information.

Here is how social proof works in the B2B setting. If there are few existing buyers on an exchange, we expect a prospective buyer to be less inclined to participate in the exchange. The lack of other buyers increases his uncertainty about the exchange, even though it is advantageous to him when only few other buyers are participating. (Like a restaurant seeker who, on seeing an empty restaurant, walks by it even though she might think service will be fast!). As the number of buyers increase, the prospective buyer sees evidence of quality and is more inclined to participate in the exchange. Although competition and prices increase with more buyers, the positive signal of quality from the participation of other buyers matters more. However, like a restaurant seeker who sees a crowded restaurant, our buyer will be deterred from participating in an overly crowded exchange when competition is too intense and prices are too high. This predicted pattern is different from an information cascade, which draws each succeeding buyer in as he views the actions of others. In our social proof case, the buyer is more like Yogi Berra, who said approximately “Nobody goes there anymore, it’s too crowded.”

**Business-to-Business (B2B) Exchanges**

The context of this study is B2B exchange networks, such as Alibaba.com, ECEurope.com and ECPlaza.com. These exchanges function as market-aggregators, -makers and -facilitators (Bakos 1998; Dai and Kauffman 2002). They increase the pool of potential trading partners for buyers and suppliers by creating centralized marketplaces (Spulber 1999), and help firms extend their reach globally

Membership fees represent the main source of revenue for most B2B exchanges. For example, almost 97% of Alibaba.com’s US$570 million in revenue is from membership packages. Most B2B exchanges currently do not charge transaction-based fees because they cannot reliably observe transactions that take place between buyers and suppliers (Rochet and Tirole 2006; Roson 2005). Fixed access fees affect the number of customers joining the platform while variable usage fees affect the volume of interactions between members of the platform (Evans and Schmalensee 2007). Fixed membership fees (in contrast to per-transaction charges) allow buyers and suppliers to retain the benefits of their transactions on the exchanges. This fee structure results in stronger inter-network externalities and makes getting and keeping both sides on board even more critical to the exchanges’ success (Armstrong 2006).

Membership revenues in many B2B exchanges are mainly generated on the supplier-side of the platform. Exchanges usually provide free memberships to buyers, while allowing suppliers to choose between free or paid memberships. Suppliers who upgrade to paid memberships enjoy additional and/or enhanced services beyond those that come with free memberships. This business model, in which a platform charges the two sides different prices, is common in two-sided markets to address the “chicken-and-egg problem” discussed above. Many platforms adopt pricing structures that are heavily skewed towards one side of the market; and generally, the side that enjoys greater inter-network externalities is more likely to face higher prices than the side that experiences lower inter-network externalities (Evans 2003).

It is the presence of buyers that gives rise to inter-network externalities and help B2B exchanges generate revenues from suppliers. Hence exchanges compete by attracting both suppliers and buyers. In fact,

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3 Based on Alibaba.com’s 2009 Annual Report, available at http://ir.alibaba.com/ir/home/financial_reports.htm (last accessed in September 2010). Its total revenue is RMB3,875 million, and membership-based revenue is 96.8% (see page 28 of the Annual Report). Exchange rate: RMB 1 = US$0.1476. Although information on the revenue sources of other B2B exchanges is not publicly available, an examination of the services offered by other exchanges indicates that membership packages are key revenue drivers.
competition for buyers can be quite intense as many buyers frequently participate in multiple exchanges simultaneously (i.e., multi-homing).\textsuperscript{4} A key implication of multi-homing among buyers is that B2B exchanges not only have to compete to get more buyers to use their platform, but also to get these buyers to prefer their exchanges to others.

**MULTI-HOMING USERS’ PREFERENCES FOR EXCHANGE NETWORKS**

Multi-homing users’ preferences can be inferred from their relative usage of different platforms. All else equal, users would participate more actively on their preferred platform relative to other platform(s) in which they are participating. We assume that preference between two platforms A and B is shown when platform A is chosen more often than platform B. Therefore, the preference for A over B is indexed by the relative proportion of times A is chosen over B. This is conceptually similar to classical methods for measuring preferences in psychology and marketing (Coombs \textit{et al.} 1970; Thurstone 1927).

Our theoretical framework in explaining multi-homing users’ preferences for exchanges is as follows. We theorize that inter- and intra-network externalities affect perceived usefulness of exchanges, and these perceptions in turn affect multi-homing users’ preferences for exchanges. Inter-network activity levels have direct, positive impacts on platforms’ perceived usefulness and users’ preferences. The impacts of intra-network activity levels on platforms’ perceived usefulness and users’ preferences depend on the levels of activity. At high intra-network activity levels, same-side competition among users is more salient and it has direct, negative impacts on platforms’ perceived usefulness and users’ preferences. However, at low intra-network activity levels, the social proof effect is relatively more important to users, and it has indirect, positive impacts on platforms’ perceived usefulness and users’ preferences. (Presently we do not have sufficient theoretical rationale to relate network externalities with perceived ease of use, the other key determinant of system usage in Technology Acceptance Model. Instead, we control for multi-homing users’ perceptions of the ease of use of the respective systems in our model specifications.)

\textsuperscript{4} Similarly, suppliers can and often multi-home on various exchanges. Walczak \textit{et al.} (2006) find that sellers use multiple auction platforms to get greater market exposure and reach a larger variety of buyers.
Users’ Preferences and Inter-Network Activity Levels

On exchange networks, inter-network activities are undoubtedly important to users’ decisions to adopt the platform. After all, users join an exchange for the expected benefits from interacting with users on the opposite side. This expectation is related to the platform’s perceived usefulness (Davis 1989). Therefore, when users need to decide which exchange(s) to join, they are likely to choose among those with high inter-network activity levels (Caillaud and Jullien 2003).

For multi-homing users, inter-network activity levels should continue to be an important consideration even after they have joined and become familiar with a platform. As these users have limited resources (e.g. time, attention) and multiple exchange networks to choose from on any occasion, they are likely to prioritize and actively use beneficial ones more. Furthermore, because they are using multiple exchanges, they are by definition not locked into a specific exchange. As such, multi-homing users will reduce the use of “under-performing” exchanges.

Thus the relative levels of inter-network activity in various exchange networks can affect multi-homing users’ long-term system usage decisions and behaviors. We hypothesize a positive relationship between inter-network activity levels and users’ preferences for two-sided exchanges networks: users prefer and use more of those exchanges that have higher levels of activity on the opposite sides.

H1: A positive relationship exists between users’ preferences for exchange networks and inter-network activity levels.

Users’ Preference and Intra-Network Activity Levels

Some two-sided network studies suggest that intra-network externalities on exchanges are negative due to competition effects (e.g. Anderson et al. 2008; Belleflamme and Toulemonde 2009; Tucker and Zhang 2010). For example, competition among buyers intensifies as the buying activity level on an exchange increases. Heightened competition among buyers allows suppliers to raise prices, and reduces the benefits
that buyers derive from participating in the exchange. When this happens, buyers are likely to seek other exchanges where they might find better prices. Similarly, price competition among suppliers increases with selling activity level on an exchange, and suppliers may be driven out when the competition is too high. Therefore, due to same-side competition on the platform, higher intra-network activity levels have direct and negative effects on users’ perceived usefulness of an exchange. Such negative intra-network externalities imply users’ preferences for exchanges would be inversely related to the level of intra-network activities (Belleflamme and Toulemonde 2009).

However, the relationship between users’ preference and intra-network activity might not be linear. Competitive interactions among users on the same side of a network should occur at high levels of intra-network activity. Ceteris paribus, suppliers have greater power to raise prices when there is much buying going on in the exchange. At low levels of intra-network activity, competitive effects should be relatively weaker. In addition, a different type of process among users on the same side may be occurring. Specifically, a certain level of intra-network activity must take place to motivate individual users to participate on the platform. This phenomenon can be explained by the principle of social proof, which states that observations of other people’s behaviors affect one’s decisions (Cialdini 2008).

Social proof is particularly salient under two conditions (Cialdini 2008), both of which often occur in two-sided exchange networks. The first is the similarity of other people to oneself. We are motivated to act like those we observe when we are similar to them. The nature of two-sided networks is such that a clear boundary separates one type of user from another on the platform. For instance, there are buyers and suppliers in online exchanges, and borrowers and lenders in social lending networks. In these examples, it is obvious to individual users which side they are on, and whether another user is on the same side. The second condition required for social proof is when there is uncertainty. In two-sided exchange networks, users’ interactions with the opposite side often involve some uncertainty. Buyers on exchanges may be unsure about the suppliers’ trustworthiness, while lenders in social lending networks are concerned with
borrowers’ credit worthiness. Such uncertainty is present whenever the user initiates interactions with another user on the other side of the platform.

An important point in the social proof principle is that what matters is not just the presence or number of others people that an individual observes; rather it is the actions of other people that the individual observes that influence his behaviors (Cialdini 2008). Hence in our two-sided exchange network context, it is important to consider not the number of other users on the same side per se, but what these users do: the intra-network activity level. If other users on the same side actively use a platform, a user would be more motivated to do the same. Here, we see that intra-network activity levels have indirect and positive impacts on perceived usefulness of an exchange. Yet this positive social proof effect is likely to increase at a diminishing rate with respect to the number of observed actions of others. The initial observations of other users’ behaviors should provide significant informational value about the platform. Beyond a certain level, additional observations would add little to what a user has already inferred.

We therefore hypothesize a non-linear relationship between users’ preferences for exchanges and intra-network activity levels. At low intra-network activity levels, the competitive effect is relatively weak. At the same time, increases in activity levels on an exchange signal other users’ positive evaluation of the exchange, leading to higher usage of and preferences for it. However, because there is an upper bound to the influences of social proof, beyond certain levels of intra-network activity, further increases in activity levels have minimal incremental effects. Instead, such increases would raise the competition among users on the same side. Since multi-homing users have alternative exchanges that they can turn to, their usage of and preferences for this particular exchange are likely to decrease.

H2: Users’ preferences for exchanges increase at a decreasing rate with respect to intra-network activity levels.

METHOD AND ANALYSIS
Data Collection

To test our hypotheses, we observe buyers’ usage on two exchanges over a seven-month period. On both exchanges, buyers can post an unlimited number of buying requests for free, whereas the number of selling leads suppliers can post depend on their membership type (free or paid) on the exchanges. There are further complications on the supplier side of the platforms, as both exchanges offer multiple categories of paid memberships with different limits on the number of selling leads.\textsuperscript{5} We therefore focus on buyers’ usage so that our results are not confounded by system constraints due to different membership categories. Some existing two-sided network research also examines one side of the platforms only (e.g. Tucker and Zhang 2010). Since buyers’ and suppliers’ motivations and behaviors are relatively symmetric on exchanges, our hypotheses should hold in general for users on both sides of the platforms, and there is no significant loss in generalizability or validity by limiting our focus on buyers’ behaviors.

We collected data from two relatively popular horizontal exchanges between July 2009 and February 2010. The two exchanges have similar Alexa site popularity rankings.\textsuperscript{6} (We could not collect data from the most popular exchange according to Alexa rankings, as that exchange blocked certain information from non-registered users.\textsuperscript{7} This constraint would have affected our identification of multi-homing buyers, as we discuss below. However, not using data from the most popular exchange is not a problem since our theory and models explicitly account for site usage, which are indicators of site popularity.) Both exchanges cover multiple industries such as chemicals, computers, and electronics. Each industry on the exchanges is further segmented into various product categories. For instance, the chemical industry segments include inorganic and pharmaceutical chemicals. Both exchanges offer free memberships and

\textsuperscript{5} On one of the exchanges, suppliers on free membership can post up to 20 selling leads, while those on paid memberships can post up to 200 or infinite number of selling leads (depending on the membership category). On the other exchange, suppliers on free membership can post up to 50 selling leads, while those on paid memberships have a limit of 200 or 1,000 selling leads (depending on the membership category). However, both exchanges offer free membership to buyers, who can post unlimited number of buying requests.

\textsuperscript{6} In June 2010, the two exchanges ranked second and third in Alexa’s site popularity for “Import and Export Portals” category.

\textsuperscript{7} Since we are not involved in corporate sales or purchasing activities, we could not register with the B2B exchange without providing fake information.
similar services for buyers. Buyers can create a company profile page and post their buying requests on the exchanges. They can also view suppliers’ profiles and selling leads posted by suppliers.

Data were collected 4 times at 2-month intervals. At time 1, we retrieved buying requests posted in all product categories by buyers on both exchanges. We did this on a daily basis for one month. By the end of one month, we identified 690 buyers in Exchange A and 902 buyers in Exchange B who posted at least one buying request. For each of these buyers, we gathered information about the number of buying requests they posted, as well as the number of selling leads, buying requests, and suppliers on paid membership in the product category that the buyer was in. We also obtained the date on which the buyer registered with the respective exchanges to calculate membership tenure, which is the difference between the date she joined an exchange and the date on which she is added to our dataset.

Appendix A shows samples of buying requests posted in Exchange A and Exchange B. To identify multi-homing buyers, we matched the buying requests on both exchanges by comparing each buyer (e.g. company name, address, country, and contact information) and their buying requests (e.g. product requested, product category, and product description). Buyers are considered to be multi-homing if they posted the same buying request in both exchanges in the first time period. On average, buyers in our dataset posted the same buying request in both exchanges less than 4 days apart, with 50% of buyers posting the same buying request in both exchanges on the same day. By the end of first time period, we identified 118 multi-homing buyers in our dataset. This represents 17.1% and 13.1% of buyers that posted a buying request in the respective exchanges during the first time period. These percentages are conservative estimates of multi-homing buyers in our sample, since buyers could also be using other exchanges beside either of the two exchanges that we use in this study. The percentages of multi-homing buyers could also be affected by the exchanges’ popularity (proxied by Alexa site popularity ranking). For some buyers, being in popular platforms may negate their need to use other platforms to source for suppliers. This is consistent with the observations in Walczak et al.’s (2006) survey of online auction sellers in eBay, Amazon, and Yahoo. In that study, 10% of respondents in eBay, which is the most
popular among the three auction platforms, indicated that they use multiple auction sites. In contrast, 53% and 74% of respondents in Amazon and Yahoo, respectively, use multiple auction sites.

In subsequent time periods, we collected data on buyers’ usage (number of buying requests posted) and network characteristics (number of selling leads, buying requests, and supplier on paid memberships in the relevant product categories). At the end of the data collection stage, we had 472 observations of 118 buyers in 79 product categories over 4 time periods.

The distribution of the buyers’ tenure in the respective exchanges in the first time period is shown in Table 2. In each exchange, almost 55% of buyers have more than one year of experience with the platform when we included them in our dataset in the first time period. The average membership tenure of buyers in Exchange A and Exchange B was 837 and 827 days, respectively; the median membership tenure of buyers was 498 and 407 days, respectively. The difference in the median buyer’s registration dates on the two exchanges is approximately 15 days. These statistics indicate that the buyers have relatively similar experiences with both exchanges, and our sample has a good mix of new and experienced users of the two exchanges.

Table 2: Frequency Distribution of Buyers’ Membership Tenure

<table>
<thead>
<tr>
<th>Membership tenure in First Time Period</th>
<th>Exchange A</th>
<th>Exchange B</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 days or less</td>
<td>16 (13.6%)</td>
<td>19 (16.1%)</td>
</tr>
<tr>
<td>Between 30 and 89 days</td>
<td>13 (11.0%)</td>
<td>14 (11.9%)</td>
</tr>
<tr>
<td>Between 90 and 179 days</td>
<td>13 (11.0%)</td>
<td>13 (11.0%)</td>
</tr>
<tr>
<td>Between 180 and 359 days</td>
<td>12 (10.2%)</td>
<td>9 (7.6%)</td>
</tr>
<tr>
<td>360 days or more</td>
<td>64 (54.2%)</td>
<td>63 (53.4%)</td>
</tr>
<tr>
<td>Average Tenure</td>
<td>837 days</td>
<td>827 days</td>
</tr>
<tr>
<td>Median Tenure</td>
<td>498 days</td>
<td>407 days</td>
</tr>
</tbody>
</table>

Model Specification

To model buyer behavior, we adapt the model specification in Chevalier and Mayzlin’s (2006) study of the effects of consumer reviews on relative sales of books on two online booksellers. We specify the
number of buying requests posted in each exchange by a multi-homing buyer as a function of (i) the number of selling leads posted by suppliers, and (ii) the number of buying requests posted by other buyers in the relevant product category. Since buyers are multi-homing, we allow the characteristics of each exchange to affect individual buyers’ usage in the other exchange. Equations 1 and 2 show the function of buying requests posted by a buyer in Exchange A and Exchange B, respectively:

\[
\log (\text{Request}_i^A) = \alpha_1 \log(\text{Selling}_i^A) + \alpha_2 \log(\text{Buying}_i^A) + \alpha_3 \log(\text{Buying}_i^A)^2 \\
+ \alpha_4 \log(\text{Selling}_i^B) + \alpha_5 \log(\text{Buying}_i^B) + \alpha_6 \log(\text{Buying}_i^B)^2 \\
+ X_i^A + v_i^A + C_i + \mu_i^A
\]  

\[
\log (\text{Request}_i^B) = \beta_1 \log(\text{Selling}_i^A) + \beta_2 \log(\text{Buying}_i^A) + \beta_3 \log(\text{Buying}_i^A)^2 \\
+ \beta_4 \log(\text{Selling}_i^B) + \beta_5 \log(\text{Buying}_i^B) + \beta_6 \log(\text{Buying}_i^B)^2 \\
+ X_i^B + v_i^B + C_i + \mu_i^B
\]  

where superscripts A and B refers to Exchange A and Exchange B, respectively; Request$_{i,t}$ represents the number of buying requests posted by buyer $i$ in period $t$; Selling$_t$ is the number of selling leads posted in the relevant product category in period $t$; Buying$_{i,t}$ is the number of buying requests posted by all buyers (excluding buyer $i$) in the relevant product category in period $t$; $X_i$ is a vector of variables to control for heterogeneity between the exchanges and among individual buyers in period $t$; $v_i$ is the unobserved time-invariant exchange effect; and $C_i$ is the unobserved individual effect. We use a log specification in our models as the data in their original form have high skewness and kurtosis. For instance, the numbers of buying requests posted in Exchange A and Exchange B by individual buyers have skewness greater than 3.0 and kurtosis greater than 20.0. After log-transformation, the skewness and kurtosis are closer to those in normal distributions: skewness is now between .4 and .9 and kurtosis is between 3.0 and 4.5.

The unobserved individual effect, $C_i$, in Equations 1 and 2 accounts for factors such as a user’s computer self-efficacy and anxiety, which might affect perceptions of the exchanges’ ease of use as well as his usage of the exchanges (Venkatesh 2000). To eliminate these unobserved effects, we difference Equations 1 and 2. By doing so, we also eliminate any industry-level effects that may influence both the network
characteristics and users’ preferences. For instance, an industry shock may affect both the numbers of selling leads and buying requests posted in both exchanges, as well as individual buyers’ purchase needs. Equation 3 shows the differenced equation:

\[
\text{Pref}_B = \gamma_1 \log(\text{Selling}_A) + \gamma_2 \log(\text{Buying}_A) + \gamma_3 \log(\text{Buying}_A^2) \\
+ \gamma_4 \log(\text{Selling}_B) + \gamma_5 \log(\text{Buying}_B) + \gamma_6 \log(\text{Buying}_B^2) \\
+ X_i \Pi + (v_i^B - v_i^A) + \mu_{i,t}
\]

(3)

where \( \gamma_j = \beta_j - \alpha_j \), and \( \text{Pref}_B = \log(\text{Request}_B^i) - \log(\text{Request}_A^i) = \log \left( \frac{\text{Request}_B^i}{\text{Request}_A^i} \right) \). The term in the parentheses denotes the ratio of the buying requests posted in Exchange B to those posted in Exchange A by buyer \( i \). We treat this ratio as a proxy of buyer \( i \)'s revealed preference for Exchange B. The log specification in our model ensures the dependent variable is symmetric. Our measure of buyer preference is conceptually similar to the constant-sum scale measure in marketing research (e.g. Amir and Levav 2008; Carpenter and Nakamoto 1989; Griffin and Hauser 1993), where an individual’s preferences are expressed as ratios of points allocated to different options. However, instead of asking users to allocate points, we observe their relative usages of various options (in this case, the respective exchanges). This approach is appropriate as we assume users reveal their preference pattern by their market behaviors (Samuelson 1948).

We assume the unobserved exchange effects, \( v_i^A \) and \( v_i^B \), are time-invariant.\(^8\) The difference in the exchange effects in Equation 3 will bias estimates of the parameters if it is non-zero. To address this, we use a panel structure for our data and estimate our models using fixed effects (Wooldridge 2002). As the product category is time-invariant, we cannot introduce a dummy variable for each product category using a fixed effects model. Instead, we cluster our observations by the product category to which buyers belong so as to appropriately adjust the standard errors (Wooldridge 2002).

\(^8\) Both exchanges did not give any press releases during our data collection period. This indicates that no major initiatives were launched during this period by the exchanges, and supports our assumption that the unobserved exchange effects are time-invariant.
A possible concern in our setting is that buying and selling activity levels could be jointly determined. However, in our case, individual buyers’ preferences for the exchanges (which is represented by the ratio of buying requests posted in Exchange B to those posted in Exchange A by individual buyers) likely have minimal effects on selling activity levels. Suppose a supplier in Exchange A does not use Exchange B. This supplier would not observe the buyers’ usage on Exchange B and his decision to post selling leads would not be affected by the buyers’ preferences for Exchange B. Suppose another supplier participates on Exchange A and Exchange B, and she observes the buyers’ relative usage on both exchanges. We assume that this supplier should be more interested in the buying activities from all buyers in the exchanges rather than from just the buyers in our sample, which constitute less than 20% of all buyers who posted buying requests in each exchange during our data collection. Even if this supplier is only interested in the preferences of buyers in our sample, she is likely to consider the preferences of these buyers collectively rather than individually. Therefore, by using individual buyers’ preferences for the exchanges as the dependent variable in Equation 3, we minimize the problem of simultaneity between buying and selling activities on the exchanges in the model.

Controls. Online exchanges often promote suppliers who have paid memberships on the platforms. For example, exchanges typically highlight suppliers who have paid memberships by giving them priority listing or emphasizing their company profiles. Different membership categories may affect buyers’ relationships with suppliers on the platforms (e.g. Koh et al. 2009) and their preferences for exchanges. We control for the number of suppliers with paid memberships in the respective product categories on each of the exchanges (Paidi). In addition, to account for systematic differences in buyers’ preference across time, we add three time period dummies (d2, d3, d4) in Equation 3. Finally, since system usage may be affected by users’ experiences with the platforms, we control for individual buyers’ membership tenure in the exchanges (Tenurei).

RESULTS AND ANALYSES
Main Results

Table 3 presents the descriptive statistics and correlation matrix of the variables across time periods ($N = 472$; 4 observations per buyer). Buyers’ tenure in both exchanges correlates very highly in our dataset ($r = .94$), as they tend to join the exchanges around the same time. This implies that it may be sufficient to use the buyers’ membership tenure in one exchange when controlling for their experiences with the two platforms. We therefore drop the buyer’s membership tenure in Exchange B from our Equation 3 to avoid multicollinearity. The selling and buying activities between the two exchanges are only moderately correlated ($r = .15$ and $r = .25$, respectively), suggesting that activities in both exchanges do not overlap sufficiently to lead to identification issues.

Table 3: Descriptive Statistics and Correlation Matrix

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preference for Exchange B</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Selling leads (Exchange A)</td>
<td>-0.10</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buying requests (Exchange A)</td>
<td>-0.14</td>
<td>0.60</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Selling leads (Exchange B)</td>
<td>0.09</td>
<td>0.15</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buying requests (Exchange B)</td>
<td>-0.04</td>
<td>-0.01</td>
<td>0.25</td>
<td>0.30</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paid-membership suppliers (Exchange A)</td>
<td>0.00</td>
<td>0.75</td>
<td>0.34</td>
<td>0.26</td>
<td>-0.11</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paid-membership suppliers (Exchange B)</td>
<td>0.11</td>
<td>0.13</td>
<td>-0.09</td>
<td>0.83</td>
<td>0.23</td>
<td>0.28</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buyer's membership tenure (Exchange A)</td>
<td>0.09</td>
<td>0.06</td>
<td>-0.02</td>
<td>-0.06</td>
<td>-0.04</td>
<td>0.02</td>
<td>-0.07</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Buyer's membership tenure (Exchange B)</td>
<td>0.10</td>
<td>0.05</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.04</td>
<td>0.01</td>
<td>-0.05</td>
<td>0.94</td>
<td>1.00</td>
</tr>
<tr>
<td>Mean</td>
<td>0.00</td>
<td>2.96</td>
<td>1.78</td>
<td>3.81</td>
<td>2.61</td>
<td>0.66</td>
<td>1.15</td>
<td>2.71</td>
<td>2.67</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.25</td>
<td>0.80</td>
<td>0.73</td>
<td>0.39</td>
<td>0.41</td>
<td>0.53</td>
<td>0.40</td>
<td>0.59</td>
<td>0.61</td>
</tr>
</tbody>
</table>

$N = 472$ (4 observations per buyer). All variables are log-transformed.

We estimate Equation 3 with fixed effects at the buyer level. Table 4 shows the results from this regression. Using the Sargan-Hansen statistic, we reject the null hypothesis that the orthogonality assumption is valid ($p < .01$), supporting our use of fixed effects. In addition, to compare the fixed effects

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9 If the orthogonality assumption is not satisfied (i.e. unobserved effects do correlate with independent variables), random effects estimators are not consistent but fixed effects estimators are. However, if the orthogonality assumption is satisfied, random effects estimators are consistent and also more efficient than fixed effects estimators. The Sargan-Hansen test statistic is a heteroskedastic- and cluster-robust form of a Hausman test that compares random effects and fixed effects estimators (Schaffer and Stillman 2010). To run the Sargan-Hansen test, we use the fixed effect transformation model (Wooldridge 2002) where we demean Equation 3 across observations for each buyer to eliminate the difference in unobserved exchange effects. Rejection of the null hypothesis in the Sargan-Hansen test (as in our case) implies using random effects is not appropriate.
model with the pooled OLS model, we estimate the fixed effects without clustering the observations by product category. The F-test rejects the null hypothesis that the fixed effects are zero (F-statistics = 10.25, \( p < .001 \)), indicating that using fixed effects is appropriate.

### Table 4: Main Results

<table>
<thead>
<tr>
<th>DV: Preference for Exchange B</th>
<th>Regression 1 Coeff.</th>
<th>Regression 2 Coeff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma_0 ): Constant</td>
<td>-1.73 (1.16)</td>
<td>-1.70 (1.13)</td>
</tr>
<tr>
<td>( \gamma_1 ): ( \log(\text{Selling}_t^A) )</td>
<td>-0.11* (0.06)</td>
<td>-0.11* (0.06)</td>
</tr>
<tr>
<td>( \gamma_2 ): ( \log(\text{Buying}_{it}^A) )</td>
<td>-0.06 (0.16)</td>
<td>-0.06 (0.16)</td>
</tr>
<tr>
<td>( \gamma_3 ): ( \log (\text{Buying}_{it}^A)^2 )</td>
<td>0.02 (0.10)</td>
<td>0.02 (0.10)</td>
</tr>
<tr>
<td>( \gamma_4 ): ( \log(\text{Selling}_t^B) )</td>
<td>0.54* (0.31)</td>
<td>0.54* (0.30)</td>
</tr>
<tr>
<td>( \gamma_5 ): ( \log(\text{Buying}_{it}^B) )</td>
<td>1.87* (0.73)</td>
<td>1.87* (0.73)</td>
</tr>
<tr>
<td>( \gamma_6 ): ( \log (\text{Buying}_{it}^B)^2 )</td>
<td>-0.67* (0.26)</td>
<td>-0.67* (0.26)</td>
</tr>
<tr>
<td>( \gamma_7 ): ( \log(\text{Paid}_t^A) )</td>
<td>-0.08 (0.05)</td>
<td>-0.07 (0.05)</td>
</tr>
<tr>
<td>( \gamma_8 ): ( \log(\text{Paid}_t^B) )</td>
<td>-0.15 (0.14)</td>
<td>-0.15 (0.14)</td>
</tr>
<tr>
<td>( \gamma_9 ): ( d2 )</td>
<td>-0.01 (0.03)</td>
<td>-0.01 (0.03)</td>
</tr>
<tr>
<td>( \gamma_{10} ): ( d3 )</td>
<td>-0.01 (0.04)</td>
<td>0.00 (0.05)</td>
</tr>
<tr>
<td>( \gamma_{11} ): ( d4 )</td>
<td>0.00 (0.05)</td>
<td>0.01 (0.05)</td>
</tr>
<tr>
<td>( \gamma_{12} ): ( \log(\text{Tenure}_{it}^A) )</td>
<td>0.00 (0.03)</td>
<td>0.05 (0.10)</td>
</tr>
<tr>
<td>( \gamma_{13} ): ( \log(\text{Tenure}_{it}^B)^2 )</td>
<td>—</td>
<td>-0.02 (0.04)</td>
</tr>
</tbody>
</table>

F-statistics \( p < .001 \) \( p < .001 \)
Adjusted R\(^2\) 0.716 0.715
\( N = 472 \). Robust standard errors in parenthesis. * \( p < .10 \) * \( p < .05 \)

Note: The estimates for individual buyer dummies are “suppressed” from the results and not shown.

As shown in Table 4 (Regression 1), the level of selling activity in Exchange A has a significant negative effect on buyers’ preferences for Exchange B (\( \gamma_1 = -.11, p < .10 \)), while the level of selling activity in Exchange B has a significant positive effect on buyers’ preferences for Exchange B (\( \gamma_4 = .54, p < .10 \)).

These results demonstrate positive inter-network externalities, and support H1. In addition, the level of buying activity in Exchange B has a significant non-linear relationship with buyers’ preferences for Exchange B (\( \gamma_5 = 1.87, p < .05 \) and \( \gamma_6 = -.67, p < .05 \)), supporting H2. Buyers’ preferences for Exchange B initially increase with increasing buying activity level in the exchange, but decrease at higher buying levels, consistent with our integration of social proof and competition effects. Although the signs of the
estimators for buying activity level in Exchange A are in the expected direction, they are not statistically significant ($\gamma_2 = -.06, p > .10$ and $\gamma_3 = .02, p > .10$).

Recall that a buyer’s preference for Exchange B refers to her use of Exchange B over that of Exchange A. Higher relative usage of Exchange B would lead to a higher value of buying requests in Exchange B than in Exchange A. Suppose every multi-homing buyer in our sample posts 5 buying requests in Exchange A and the average value of each request is $30,000.\textsuperscript{10} A 1\% higher relative usage of Exchange B implies that the value of buying requests in Exchange B is greater than that in Exchange A by $177,000 (5 \times $30,000 \times .01 \times 118)$. According to the results in Table 4, ceteris paribus, a 1\% increase in selling activities in Exchange A lowers relative usage of Exchange B by the multi-homing buyers by .11\% ($19,470$ less buying requests in Exchange B), whereas a 1\% increase in selling activities in Exchange B raises relative usage of Exchange B by these buyers by .54\% ($95,580$ more buying requests in Exchange B). Table 5 shows the change in relative usage of Exchange B and corresponding additional values of buying requests posted by the multi-homing buyers at various levels of requests posted by other buyers in the exchange.

<table>
<thead>
<tr>
<th>Change in relative usage of Exchange B</th>
<th>Additional value of buying requests in Exchange B</th>
</tr>
</thead>
<tbody>
<tr>
<td>+.53%</td>
<td>$+$93,810</td>
</tr>
<tr>
<td>+.13%</td>
<td>$+$22,412</td>
</tr>
<tr>
<td>-.41%</td>
<td>$-$71,972</td>
</tr>
<tr>
<td>-.81%</td>
<td>$-$143,370</td>
</tr>
</tbody>
</table>

Note: We assume each multi-homing buyer in our sample initially posts 5 buying requests in both exchanges, and the purchase value of each request is $30,000.

Robustness checks. As a key premise of this study is to examine system usage by new and experienced users, we checked whether our results are sensitive to different specifications of buyers’ experiences with the exchanges. First, we added a quadratic term for buyers’ tenure in Exchange A to detect possible non-

\textsuperscript{10} Buyers in the two exchanges do not state the purchase values in their buying requests. Our estimates are based on Koh et al.’s (2009) survey of buyers in a similar B2B exchange, in which the median purchase value is $30,000.
linear relationships between membership tenure and buyers’ preferences (Regression 2 in Table 4).
Second, instead of using continuous variables for buyers’ membership tenure, we classify whether a buyer is new to the exchange using by a dummy variable. For example, we treat a buyer as a new user if her membership tenure is less than 30 days. We also use different criteria for a new user, such as when the membership tenure is not greater than 90, 180, 360 days. The results are similar across these different specifications: buyers’ preferences for the exchanges are positively related to selling activities, and non-linearly related to buying activities. The results are also similar when we use buyers’ membership tenure in Exchange B or in both exchanges.\footnote{In the interest of space, the results using dummy variable for new members, and buyers’ membership tenure in Exchange B or both exchanges are not shown. These results are available from the authors.}

**Counterfactual Analyses**

Our analysis is based on the assumption that multi-homing behavior influences buyer behavior and the use of exchange networks. We want to test if this is a useful assumption. It is interesting to see how misspecifying users’ homing behaviors would affect the results and implications. In practice, exchanges may analyze their users’ behaviors without considering these users’ participation on other exchanges. In prior published work, researchers sometimes assume single-homing behaviors even though multi-homing behaviors are possible (e.g. Belleflamme and Toulemonde 2009; Chandra and Collard-Wexler 2009). We conduct counterfactual analyses by assuming (contrary to fact) the buyers in our sample are single-homing in each of the exchanges. Regressions 1a and 2a in Table 6 show the estimates of Equation 1 (buyers’ participation in Exchange A) and Equation 2 (buyers’ participation in Exchange B), respectively, with fixed effects model using dummy variable regressions. Each of these regressions assumes that the focal exchange observes the activity levels in the competing exchange, but not its users’ individual participation and membership tenure there.
## Table 6: Counterfactual Analysis Results (Dummy Variable Regression)

<table>
<thead>
<tr>
<th>Equation</th>
<th>DV: Buyers’ participation in Exchange A</th>
<th>Regression 1a</th>
<th>Regression 1b</th>
<th>DV: Buyers’ participation in Exchange B</th>
<th>Regression 2a</th>
<th>Regression 2b</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_0 ): Constant</td>
<td>2.22 (1.58)</td>
<td>0.56 (0.30)</td>
<td>( \beta_0 ): Constant</td>
<td>0.59 (1.62)</td>
<td>0.45 (1.62)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_1 ): log ((\text{Selling}_A'))</td>
<td>0.17 (0.09)</td>
<td>0.15 (0.09)</td>
<td>( \beta_1 ): log ((\text{Selling}_B'))</td>
<td>0.06 (0.07)</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>( \alpha_2 ): log ((\text{Buying}_A'))</td>
<td>-0.07 (0.29)</td>
<td>-0.05 (0.29)</td>
<td>( \beta_2 ): log ((\text{Buying}_A'))</td>
<td>-0.11 (0.26)</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>( \alpha_3 ): log ((\text{Buying}_A')^2)</td>
<td>-0.10 (0.11)</td>
<td>-0.11 (0.11)</td>
<td>( \beta_3 ): log ((\text{Buying}_A')^2)</td>
<td>-0.09 (0.12)</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>( \alpha_4 ): log ((\text{Selling}_B'))</td>
<td>-0.47 (0.44)</td>
<td>—</td>
<td>( \beta_4 ): log ((\text{Selling}_B'))</td>
<td>0.03 (0.46)</td>
<td>-0.05 (0.45)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_5 ): log ((\text{Buying}_B'))</td>
<td>0.18 (0.46)</td>
<td>—</td>
<td>( \beta_5 ): log ((\text{Buying}_B'))</td>
<td>1.94** (0.72)</td>
<td>2.29* (0.91)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_6 ): log ((\text{Buying}_B')^2)</td>
<td>-0.04 (0.17)</td>
<td>—</td>
<td>( \beta_6 ): log ((\text{Buying}_B')^2)</td>
<td>-0.67* (0.26)</td>
<td>-0.79* (0.33)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_7 ): log ((\text{Paid}_A'))</td>
<td>0.06 (0.06)</td>
<td>0.05 (0.06)</td>
<td>( \beta_7 ): log ((\text{Paid}_B'))</td>
<td>-0.02 (0.06)</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>( \alpha_8 ): log ((\text{Paid}_B'))</td>
<td>-0.11 (0.14)</td>
<td>—</td>
<td>( \beta_8 ): log ((\text{Paid}_B'))</td>
<td>-0.25* (0.14)</td>
<td>-0.22 (0.15)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_9 ): d2</td>
<td>0.07** (0.02)</td>
<td>0.05* (0.02)</td>
<td>( \beta_9 ): d2</td>
<td>0.04* (0.03)</td>
<td>0.03 (0.02)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_{10} ): d3</td>
<td>0.07* (0.03)</td>
<td>0.05 (0.03)</td>
<td>( \beta_{10} ): d3</td>
<td>0.05 (0.04)</td>
<td>0.03 (0.03)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_{11} ): d4</td>
<td>0.09* (0.04)</td>
<td>0.05 (0.03)</td>
<td>( \beta_{11} ): d4</td>
<td>0.07 (0.04)</td>
<td>0.04 (0.04)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_{12} ): log ((\text{Tenure}_A'))</td>
<td>0.03 (0.04)</td>
<td>0.02 (0.04)</td>
<td>( \beta_{12} ): log ((\text{Tenure}_A'))</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>( \alpha_{13} ): log ((\text{Tenure}_B'))</td>
<td>—</td>
<td>—</td>
<td>( \beta_{13} ): log ((\text{Tenure}_B'))</td>
<td>0.06 (0.05)</td>
<td>0.05 (0.05)</td>
<td></td>
</tr>
</tbody>
</table>

F-statistics:  
- p < .001  
- p < .10  

Adjusted R^2:  
- 0.870  
- 0.869  

F-statistics:  
- p < .001  
- p < .001  

Adjusted R^2:  
- 0.856  
- 0.854  

N = 472. Robust standard errors in parenthesis.  * p < .10  * p < .05  ** p < .01

Notes:
1. Regressions 1a and 2a assume the respective exchanges observe activity levels in competing exchanges, but they do not monitor their users’ participation in those exchanges.
2. Regressions 1b and 2b assume the respective exchanges only analyze internal data that they possess.
We find a positive relationship between selling activities and buyers’ participation in Exchange A ($\alpha_1 = .17, p < .10$ in Regression 1a), and a non-linear relationship between buying activities and buyers’ participation in Exchange B ($\beta_5 = 1.94, p < .01$ and $\beta_6 = -.67, p < .05$ in Regression 2a). These findings are consistent with what we observe in the main model (Equation 3; Table 4). However, there are three important differences between the results in the main model and those in the misspecified models. First, the estimated effect of selling activities in Exchange B on buyers’ participation is much larger and likely different from zero in our hypothesized model reported in Table 4 ($\gamma_4 = .54, p < .10$), but not in Regression 2a ($\beta_4 = .03, p > .10$). Second, while the results in our hypothesized model analysis indicate that activity levels in both exchanges affect the buyers’ relative usage of the two exchanges, the results in the misspecified models suggest that the activity levels in the competitive exchange do not affect buyers’ participation in the focal exchange ($p > .10$ for $\alpha_4$, $\alpha_5$, and $\alpha_6$ in Regression 1a, and for $\beta_1$, $\beta_2$, and $\beta_3$ in Regression 2a). Third, the presence of positive time effects in the misspecified models suggests that buyers are posting more requests in the respective exchanges over time ($\alpha_9$, $\alpha_{10}$, and $\alpha_{11}$ in Regressions 1a, and $\beta_8$ in Regression 2a). However, buyers’ relative usages on the exchanges are not systematically affected by time effects in the estimates of Equations 1 and 2.

We also estimate Equations 1 and 2 with the characteristics of the non-focal exchange excluded from the models (Regressions 1b and 2b in Table 6). This specification represents the scenario where exchanges themselves only analyze the internal data that they possess. The results in Regression 1b and 2b are similar to those in Regressions 1a and 2a, respectively. Selling activity is positively associated with buyers’ participation in Exchange A ($\alpha_1 = .15, p < .10$ in Regression 1b), and buying activities and buyers’ participation in Exchange B are non-linearly related ($\beta_5 = 2.29, p < .05$ and $\beta_6 = -.79, p < .05$ in Regression 2a).

Comparing the results in the main and counterfactual analyses, we observe two problems with the misspecified/counterfactual models. First, these models paint an incomplete picture of competition between the exchanges. The estimates of the misspecified models suggest that the buyers’ usage on one
exchange is not affected by the activities on the competing exchange. Such conclusions may cause an exchange to focus insufficiently on the activity levels in competitive exchanges. Second, the differences in the results between the main model and the two misspecified models are not consistent — inter- and intra-network activity levels are each significant in one exchange but not the other when we analyze the misspecified models. As such, it is difficult for both practitioners and researchers to know a priori how a wrong assumption of homing behaviors would affect the results. This could lead to sub-optimal strategies and behavior. For instance, based on the counterfactual analyses (Regression 2a and 2b), Exchange B may not focus on increasing selling activities and instead may divert its resources to other areas on the exchange to increase its buyers’ participation. However, according to the estimates of Equation 3 (Table 4), increasing selling activity level has a positive effect on buyers’ relatively usage on Exchange B.

DISCUSSION

This study changes our understanding of system usage in two-sided networks by both new and experienced users. We find that multi-homing users’ preferences for an exchange are positively associated with its inter-network activity levels. We further find that there are two opposing effects of increasing intra-network activity: (i) a positive social proof effect, and (ii) a negative competition effect. Consequently, the relationship between multi-homing users’ preference and intra-network activity is curvilinear. As intra-network activity levels on an exchange increase, users’ preferences for this exchange initially increase and subsequently decrease. This result is surprising since economic theory suggests that higher activity levels on the intra-network side should increase competition among users and reduce their benefits to participating on the exchanges (Anderson et al. 2008; Belleflamme and Toulemonde 2009; Tucker and Zhang 2010). Our explanation for the non-linear relationship is that there are positive effects of some competition among users on the same side that stem from social proof.

Our study complements the extant research, which typically examines system usage by individuals who may be unfamiliar with newly introduced technologies (e.g. Bajaj and Nidumolu 1998; Venkatesh and
Davis 2000; Venkatesh and Morris 2000). Also, instead of looking at one-sided technologies (e.g. Chen and Hitt 2002; Kraut et al. 1998), we focus on two-sided networks that serve distinct but inter-dependent groups of users. Such networks are proliferating — various new ventures are based on two-sided network model (e.g. social lending clubs, “deal-of-the-day” websites), and some merchants are introducing platform-type services that connect their buyers with other sellers. For example, not only does Amazon sell directly to customers, it now also provides a platform (Amazon Marketplace) for buyers and sellers to transact directly with each other. We suggest that social proof can play a robust role in such networks, an observation which has not been made in prior two-sided networks research.

Although multi-homing behaviors have been discussed in two-sided networks research for some time (e.g. Armstrong 2006; Rochet and Tirole 2006), there is very little empirical work that looks at multi-homing. One exception is Jin’s and Rysman’s (2010) study that examines dealers’ multi-homing behaviors in sportcards conventions. However, Jin and Rysman (2010) do not have direct data on whether dealers single-home or multi-home; instead, they infer dealers’ single- vs. multi-homing decisions from (i) convention prices and (ii) the interaction of distances between conventions and dealers costs to participate on multiple conventions. In contrast, we observe buyers’ multi-homing behaviors directly. In addition, we focus on non-price factors in this study. This emphasis complements other studies that look at how platforms can adopt different pricing structures to motivate users’ participation (Armstrong 2006; Caillaud and Jullien 2003; Jin and Rysman 2010; Rochet and Tirole 2003, 2006).

It is possible that the phenomenon we observe on the intra-network side of exchanges is explained by something other than social proof. Since both of the exchanges from which we gathered data in this study are relatively popular (based on Alexa site popularity ranking), one can argue that users on these exchanges are not concerned with what other users are doing. Instead, these exchanges’ popularity may provide sufficient assurance to the users to overcome any uncertainty about participating in the exchanges. That is, social proof may not be necessary or salient when users are in popular platforms.
We do not believe this is likely in our setting. One must recognize that exchange popularity can be evaluated at two levels, particularly for the horizontal exchanges that we look at in this study. One level of evaluation is the popularity of the exchange as a whole, based on its media exposure (Gallaugher and Wang 2002) or website popularity ranking engines like Alexa. Another level is the popularity of the horizontal exchange for specific market segments. Just because a horizontal exchange is, by and large, popular does not mean that it is useful for buyers and suppliers in every industry or market segment. While the general popularity of an exchange might be important, what could matter more is how well suited the exchange is for specific product categories. For example, books sellers may have a stronger inclination to use Amazon Auction than eBay; even though eBay has better name recognition and higher web traffic among online auction markets, Amazon is perceived to be more efficient in the book segment (Walczak et al. 2006). In our case, although the two horizontal exchanges in this study are popular in general, we believe buyers will focus disproportionately on what other buyers in the same product categories are doing on the platforms.

There are some limitations in this study. First, by using secondary data, we can only infer users’ preferences indirectly from the data. It would further strengthen this study if we could directly establish users’ perception of the respective platforms’ usefulness as well as their preferences for the exchanges. Second, we only examine buyers’ relative usage of the two exchanges. Although suppliers’ incentives may be affected by the exchanges’ pricing strategy, we believe our hypotheses in general should also hold among multi-homing suppliers. Future research can investigate how pricing and non-price factors both affect users’ preferences in multi-homing contexts. Lastly, the B2B exchanges that we focus on in this study belong to one specific type of two-sided networks. It would be interesting to explore the extent to which our results can be generalized to multi-homing contexts in other types of non-exchange networks such as operating systems and advertisement-supported portals. For example, as interactions among users on the same sides of the platforms vary across different two-sided networks, we expect the non-linear
relationship between intra-network activity level and users’ preferences to be conditional on the specific type of network being examined.

**Theoretical Implications**

System usage by individuals who are relatively new and unfamiliar with the IT system tends to be the focal point in many studies of IT acceptance and usage. This paper highlights the need to look beyond system adoption behaviors, and examine continuous and long-term system usage. Failure to do so, particularly when users are multi-homing, may result in an incomplete, inaccurate picture of IT users’ behaviors and competition among similar systems. Our results show that although buyers multi-home on two exchanges, they may not use both exchanges equally. In fact, being the preferred platform is perhaps more crucial for two-sided networks due to inter-network externalities.

Our findings also extend the concept of social influence in users’ acceptance and usage of IT. In the Technology Acceptance Model, the relationship between social influence and system usage is often considered in a context where the users and the people who are important to them are related (e.g. colleagues and superiors), and there are direct communications between them (Devaraj et al. 2008; Venkatesh and Morris 2000; Venkatesh et al. 2003). Furthermore, the impacts of social influence on usage intention weaken as the users gain direct experiences with the systems over time (Venkatesh and Davis 2000; Venkatesh and Morris 2000). In this paper, we argue that users may be influenced by other users even in the absence of direct relationships or communications. While explicit social interactions are known to affect system usage (Sykes et al. 2009), non-explicit interactions through social proof also impact individuals’ motivation to use the systems. By observing the level of intra-network activity that is taking place on an exchange network, users can infer how other similar users might perceive the usefulness of the exchange. Moreover, we find that such social observational learning continues to be important even for long time users. On exchanges, buyers (suppliers) face persistent ex ante uncertainty
as they initiate new interactions with suppliers (buyers) on the opposite sides. As a result, a minimal level of intra-network activity is an important signal to motivate users’ participation on the exchanges.

**Managerial Implications**

Our findings also have several implications for exchange network operators. First, exchanges need to recognize the extent to which their users are multi-homing on other platforms. Multi-homing users’ participation on different exchanges affects the exchanges’ positions in users’ choice sets and competition among exchanges. As we show in the counterfactual analyses, ignoring multi-homing users’ participation on other exchanges may lead to sub-optimal strategies. Although monitoring their users’ participation on different platforms would be an ideal way to get information on these users’ behaviors and preferences, it may not be possible for exchanges to do so. A feasible alternative is for exchanges to conduct internal surveys of their users to find out about their usage on and preferences for competing exchanges. Exchanges can also learn from what some other industries are doing to observe users’ multi-homing behaviors. For instance, balance transfer services allow credit card companies to observe cardholders’ usage of other credit cards. Similarly, price-matching guarantees help retailers learn about other places where their customers shop. Exchanges can adopt similar initiatives to encourage their users to provide information about their homing behaviors.

Second, exchanges can strategically manage users’ perceptions of activity levels on both sides of the platforms. This can be challenging as users’ preferences are asymmetrically related to inter- and intra-network activity levels. On an exchange, high activity levels on side A benefit users on the opposite side B, but not necessarily users on side A. There is also a natural interplay between inter- and intra-network externalities on two-sided exchange networks, and strategies aimed at one side of the platform would
affect the opposite side indirectly. Thus, contrary to what many B2B exchanges are doing, being perceived as the largest exchange may not be the best strategy for influencing users’ preferences!12

Lastly, exchanges should consider the effects of social proof when designing and marketing their platforms. For instance, when introducing a new service, an exchange could emphasize the adoption and usage of the service by other users on the same side of the platform. This, however, does not mean that exchanges should manipulate users’ perceptions by using pseudo accounts on the platforms. In fact, such a strategy may be detrimental, as the authenticity and trustworthiness of a potential trading partner’s identity is important to users (Koh et al. 2009). Instead, exchanges can offer the new service to a core pool of active users and make these users’ activity levels salient to other users. In addition, as users look to the actions of similar users on the platform (e.g. same user-type in the same industry), exchanges should identify key industries that they want to target, and strengthen their brand recognition within these industries.

CONCLUSION

Today, individuals and businesses have many exchanges to choose from. In some cases, not only do users have multiple competing systems to choose from, they can also choose to use multiple systems at the same time. In this paper, we tackle a challenging but important research question: what affects users’ preferences when they are using multiple two-sided exchange networks. We explicitly study a situation where individuals use multiple competing systems concurrently. We also try to address the challenges presented by the dynamics of inter- and intra-network externalities on the platforms.

By observing multi-homing users’ behaviors in two exchanges over time, we find that users’ preferences for exchanges are associated with the levels of activity that take place within and across different sides of

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12 The following are claims made by some B2B exchanges (emphases added):
   2. “ECeurope is the largest source of international trade leads, rfq and tender opportunities from companies and government organizations around the world.” – www.eceurope.com
   3. “Over 4 million offers are posted in our website, which is the largest scale in the world.” – www.ecplaza.com
the platforms. These results suggest that there should be a greater emphasis on investigating multi-homing contexts and users’ preferences in future IS research. Doing so helps us to better understand the dynamics that drive system users’ behaviors and competition between technologies.
REFERENCES


Appendix A: Sample Buying Requests

Below are sample buying leads posted on the two exchanges where we collected data. To identify multihoming buyers, we compare the request details and buyer’s contact information listed in the buying requests.

Buying Request in Exchange A:

![Buying Request in Exchange A](image)

Buying Request in Exchange B:

![Buying Request in Exchange B](image)